Review on Depth Determination Bathymetry Using Remote Sensing Technique- Theoretical Appraisal

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Abstract

The determination of topography of the seabed using remote sensing technique is important in the study of oceanic/sea dynamics. This paper presents the bathymetric mapping technologies by means of satellite remote sensing (RS) with special emphasis on bathymetry derivation models, methods, accuracies. Bathymetric mapping by using echo sounding sounders could result to some constraint. However, Remote sensing (RS) technologies present efficient and cost-effective means of mapping bathymetry over remote and broad areas. RS of bathymetry can be categorized into two namely: Active and Passive RS. Active RS methods are based on active satellite sensors, which emit radiation independent of sunlight to study the earth surface or atmospheric features, e.g., light detection and ranging (LIDAR), altimeters, etc. Passive RS methods are based on passive satellite sensors, which detect sunlight (natural source of light) radiation to study earth surface e.g., multispectral or optical satellite sensors. The Stumpf's algorithm seems to perform better both in water attenuation and bottom reflectance having about 9.7% accuracy. This paper presents the development of bathymetric mapping technology by using RS, and to make most preferred preference models that can be used to determine seabed topography at a lower depth.

***Keyswords**: Bathymetric Survey, Signal Reflectance, Multispectral, Sentinel-1, Depth Extraction Algorithm.*

Introduction

For the purpose of safe navigation, marine science measures the physical characteristics of water bodies that dynamically fluctuate over time. These measurements include bathymetry as well as the shape and features of the shoreline, the characteristics of tides, currents, and waves, and the physical and chemical properties of the water (Jawak et al., 2013). Bathymetry survey measures depths to examine the topography of water bodies such as lakes, rivers, streams, and oceans (Gianinetto & Lechi, 2013). One of the foundational studies in the field of remote sensing (RS) of the maritime environment, which has many real-world applications to the coastal environment, is the measurement of bathymetry using satellite pictures.

Monitoring undersea topography, tracking the movement of deposited sediments, and creating maritime charts for navigation are just a few of the many applications that require accurate water depth determination. The management of port facilities, dredging activities, and the forecasting of channel filling and sediment budget all benefit from this knowledge (Bagheri et al., 1998). Many areas of oceanography, paleoclimate research, and marine geology depend heavily on bathymetric data. Making bathymetric maps using depth data is the process of bathymetric mapping. In a similar way to how topographic maps show the elevation of the Earth's surface at various geographic coordinates, bathymetric maps show the depth of a water body as a function of geographic coordinates (Jawak & Lius, 2014).

Lines of equal depths, or isobaths, are used to show the most common sort of bathymetric maps. To create nautical charts, shaded relief maps, and digital terrain/bathymetric models nowadays, bathymetry is mapped using echo sounders and the depth datasets are processed.

Typically, nautical charts, 3D models, and seafloor profiles are produced using bathymetric data (Guenther et al., 2000). The time it takes a laser beam or an acoustic sonar pulse to travel from the water's surface to the ocean floor and back is how ocean floor data are often gathered. This time is dependent on the speed of sound in the water, sensor characteristics, time, and other factors. The numerous bathymetry acquisition systems differ in terms of spatial resolution, coverage, temporal resolution, and data type.

Remote sensing techniques have already been developed to map bathymetry. In essence, it can be divided into two groups. The first method relies on active remote sensing data (geodetic); the second uses passive sensors and multi-spectral data. Both active and passive data approaches are emphasized in this essay. The methods used to derive bathymetry can also be divided into imaging and non-imaging categories. The two main non-imaging methods utilized for bathymetry derivation are LIDAR and satellite altimetry. LIDAR, also known as light detection and ranging, uses a single wave pulse or two waves to estimate the distance between a sensor and an ocean floor or water surface (Wang & Philpot, 1998). The round tripe of the microwave pulse from the satellite to the water bodies and back to the satellite through the analysis window is what determines the distance between the water bodies and the satellite in contrast to the distance measured by satellite altimetry (Cazenave et al., 2002). The goal of this study is to demonstrate various bathymetry techniques employing both active and passive RS while validating which is best based on existing literature.

Method/Models of Deriving Bathymetric Using Remote Techniques

I. **Optical Remote Sensing-based bathymetry:** This is based on the idea that water depth affects the overall quantity of radioactive energy reflected from a water column (Huang et al., 2001). With its inclusion of shortwave radiation with strong penetrating properties in the blue and green spectra, optical RS has an advantage. Various amounts of energy are released and captured in RS images as the incoming radiation travels through the water and is dispersed and absorbed by water molecules and other in-water components. After accounting for atmospheric corrections and water column effects, the energy the sensor receives is inversely proportional to the water depth. Indicative of the depth at which solar radiation has penetrating power is the intensity of the signal that is returned (Alphers, & Hennings, 1984).

II. **Bathymetric measurement using Multi-spectral Imagery**: This method of determining depth is thought to be relatively unreliable, particularly near coastlines, lakes, shoals, and reefs (Vogelzang et al., 1989). some of the Earth's dynamic places with the most constant change. Bathymetry data from MS/HS imagery are not accurate enough to be used for navigation. However, a cost-effective solution for bathymetry across huge areas is a system based on MS/HS imaging. There are several environmental and scientific applications for these bathymetric products. Bathymetry obtained from imagery is estimated rather than directly measured, and as a result, has a lesser degree of precision than bathymetry derived from LIDAR or multi-beam echo sounders. The usefulness of the imaging at depth is constrained by light attenuation. Because of problems with light penetration, depths deduced from aerial or satellite photos are only accurate to 25 to 30 meters, depending on the quality of the water (Jawak & Lius 2015).

III. **Bathymetry Using Hyperspectral Scanner**: More spectral discrimination power may now be applied to the coastal optics problem because to the development of HS scanners, which sample the upwelling radiance spectrum in several tens of bands with strong water penetration (Calkoen et al., 1993). In comparison to multi-spectral approaches, HS methods make it easier to distinguish between many independent environmental variables. The complexity of HS imagery exceeds that of MS imagery. Bathymetry extraction from HS images is currently a work in progress.

The higher spectral band count utilized by HS sensors makes it possible to distinguish between various elements of the water column and sea bed. However, because to this added complexity, it can only be used for research applications (jawak & Lius 2012). In comparison to what is feasible with MS sensors, the additional spectral bands improve depth determination and allow for more precise measurement of water depth and bottom type. Since most HS imagery is still gathered via airborne acquisition techniques, it lacks the benefits of satellite imagery.

IV. **Bathymetry Using Synthetic Aperture Rader (SAR)**: Using variations in the water surface, it deduces depth. This enables SAR to determine sea depth in murky aquatic situations, which was not possible with traditional remote sensing methods. Based on SAR's capacity to measure changes in sea surface height and roughness, bathymetry can be determined (Allouis, et al.,

2010). A brighter zone appears on the radar image as a result of the rougher water enhancing the radar backscatter. Knowing the tidal currents and the wind is necessary for practical SAR bathymetric measurement, as the wind's speed and direction affect the roughness modulation. The SAR imaging mechanism, according to Alphers, Hennings, and colleagues (1984), entails three steps:

1. The inflection of the surface flow speed is caused by the interface between (tidal) flow and bottom topography.
2. Surface wave spectrum deviations are caused by variations in surface flow velocity and can be predicted using the action balance equation.
3. Radar backscatter levels fluctuate due to fluctuations in the surface wave spectrum. Two-scale and initial iterations of the Bragg model it is possible to calculate the backscatter deviations using the Kirchhoff model. The advantage of SAR is that it is unaffected by cloud cover and atmospheric disturbances. Instead of producing absolute depths, it creates relative bathymetry. The method is especially well adapted to shoals and sandbanks where bathymetry is constantly changing. To determine ocean depth, SAR bathymetry readings are measured and modified, but this process has a number of intrinsic errors. Because to them, SAR-derived bathymetry is difficult to calculate and, when compared to other technologies, is intrinsically unreliable (Jawak & Lius 2014).

V. **Bathymetric Using Satellite Altimetry:** Globally, the oceans' gravity fields can be measured using satellite altimetry. To roughly determine the bathymetry of deep-seafloor features like seamounts and ridges, gravity field data can be used. When combined with data from other satellite missions, multi-satellite altimeter readings can be used to calculate the sea surface height at multiple georeferenced locations on the seafloor (Calmant, 1994). These maps can be useful for a variety of applications, such as finding barriers to the main ocean currents and shallow seamounts, despite their very low accuracy and resolution for assessing navigational risks. Plate boundaries and oceanic plateaus are also revealed by bathymetry determined from altimetry.

Models (Algorithm) For Deriving Bathymetric Survey Using Remote Sensing Technique

i. Stumpf's Model/Linear Ratio Model:

In order to circumvent the limitations of changing substrate albedo (a surface's reflecting power) when obtaining bathymetry data, Stumpf et al., 2003 created the "Ratio approach." The model, which is based on the idea that light dims exponentially with depth, suggests that the impacts of substrate albedo be reduced by employing two bands to calculate depth. Here is a mathematical explanation of this idea:

$$Z = g^{-1}\,[Ln(Ad - R_{\infty}) - Ln(R_w - R_{\infty})]$$ 1

Ad is the bottom albedo, Z is depth, g is a function of the diffuse attenuation coefficients for both downwelling and upwelling light, R is the water column reflectance if the water were optically deep, and Rw is observed reflectance. Instead of using albedo as a variable in depth derivation, the ratio model solves the problem by comparing the attenuation of two spectral bands. Several spectral bands deteriorate at various rates. As a result, depth will affect the ratio between two spectral bands. The modification in the bottom albedo should affect both spectral bands equally, but the modification in attenuation with depth will be greater than the alteration attributable to bottom albedo so that the ratio between two bands should remain comparable over different substrates at the similar depth. This can be illustrated mathematically as follows:

$$Z = m_1 \frac{Ln(nR_w(\lambda_i))}{Ln(nR_w(\lambda_J))} - m_0 \qquad 2$$

Rw is the observed reflectance, Z is depth, m1 is a constant that can be adjusted to scale the ratio to depth, n is a constant that ensures the ratio is always positive, and m0 is the offset at a depth of m0. To employ passive MS images to map shallow-water bathymetry, a number of significant challenges are addressed by the ratio transform method (Stumpf's et al., 2003).

- it does not require the removal of dark water pixels,
- the ratio transform method has fewer empirical coefficients required for the solution, which makes the method easier to use and more stable over broad geographic areas,
- the ratio method can be tuned using available reliable depth soundings. **ii.**

Jupp’s Model or Depth of Penetration Zone (DOP) Model:

Jupp's depth of penetration zone (DOP) approach is a model that is frequently used in literature to rebuild the bathymetry in coastal zones using MS data. The Jupp technique consists of two components (Jupp, 1988):

a) The computation of DOP zones, and
b) The interpolation of depths within DOP zones.
c) This method has three fundamental assumptions:
d) a) Attenuation of light is an exponential function of depth,
e) b) Water quality does not vary within an image, and
f) c) Reflective properties of the substrate are constant.

The second and third assumptions are the model's weak points because, since a satellite image typically covers a very vast area, water and bottom parameters can occasionally shift. The relative loss of radiant flux when considering a group of monochromatic light is inversely correlated with the length of the path and exhibits a lower coefficient of proportionality (extinction coefficient). Jupp's model can be written mathematically as:

$$L_e = (e^{-2kz})L_b + (1 - e^{-2k})L_w \qquad 3$$

where Le is measured at-sensor radiance, Lb is the emergent radiance from the seabed, Lw is the emergent radiance from different layers of water, z is depth, k is the coefficient of absorption. If the term Lw is hypothesized as negligible and is directly related to the quality of the water (suspended sediments) and small changes in the seabed, then, among the depth of the water column and the logarithm of the measured at-sensor radiance, there will be a linear relationship. Under these conditions, rearranging Equation (3) lead to the classical DOP equation for the water depth determination:

$$Z = \sum_{i-j}^{N} ln \frac{(L_e)i}{-2k_{tN}} - \sum_{i-j}^{N} ln \frac{(L_b)i}{-2K_{tN}} \quad 4$$

where N represents how many spectral bands there are. In reality, the DOP model expects a constant coefficient of absorption to ensure homogeneity, which is the fundamental reason why the DOP algorithm fails in some situations when the geographical lack of homogeneity is very large (jupp, 1988).

iii. **The Stratified Genetic Algorithm (SGA):** is a development of the Depth of Precision (DOP) model proposed by Jupp (1988) that states:

$$Z = \sum_{i-1}^{N} \frac{\ln(L_e)}{-2K_i N} - \sum_{i-1}^{N} \frac{\ln(L_b)i}{-2k_i N} \quad 5$$

Le is measured radiance at the sensor, Lb is radiance from the seabed, k is the absorption coefficient of the water and N is the number of spectral bands. The second term is removed and replaced with a regression coefficient (Yj) to give:

$$Z = \sum_{J-1}^{m} \frac{\ln(L_e)j - Yj}{-2Kj} \quad 6$$

where m is the number of layers. The SGA method divides the water column into levels of increasing depth and computes kj and Yj for each in order to calculate water depth. This algorithm is repeated for all spectral wavebands and those with a high correlation Coefficient is used to determine depth.

iv. **Wave Tracing Method:** Fast Fourier transformation (FFT) is a technique used to decompose a function in spatial domain into its constituent frequency components. It can be very useful while obtaining regular periodicity in the images (Baban, 1993). FFT can also be used for retrieving the wavelength and wave direction of the ocean surface waves. The FFT of a SAR sub image of N × N pixel size gives a 2-D image spectrum. The peak in this spectrum represents the mean wavelength and the mean wave direction. The wavelength and angle of propagation can be estimated using:

$$L = \frac{N\Delta X}{\sqrt{U^2 + V^2}} \quad 7$$

$$\theta = \arctan \frac{u}{v} \quad 8$$

where L is the measured peak wavelength, θ is the peak wave direction, Δx is the spatial resolution of the subset image, N is the size of the sub-image, and u and v are the coordinates of the dominant frequency with the centre point as origin.

v. **Lyzenga Model or Linear Band Model:** The amount of light reflected, which is influenced by the atmosphere, water clarity, depth attenuation, bottom reflectance, scattered suspended particles, and other factors, is what is measured by satellite RS data. Campbell described how the penetrability, bottom reflectance, and suspended material scattering of the solar spectrum vary. Thus, the RS data can be categorized using multiband radiance to improve the accuracy of water-depth estimation. Under ideal circumstances, the sea depth can be obtained from a satellite given the assumptions of a homogeneous atmosphere, identical wave situation, similar water property, and homogeneous bottom property. The satellite sensor measures the visible light reflected from the bottom after entering the water column. Beer's Law states that light attenuates exponentially with depth in the water column, and the following could be said of the connection between measured reflectance and depth:

$$R = (A_b - R_\infty)exp(-gz) + R_\infty \quad 9$$

where R∞ is the water column reflectance, if the water is optically deep, Ab is the bottom albedo, z is the depth, and g is a function of the diffuse attenuation coefficients for both down-welling and upwelling light. However, the derivation of depth from a single band is dependent on the albedo Ab, with a decline in albedo resulting in amplification in the estimated depth. Lyzenga proposed a linear solution of correction for albedo with two bands as;

$$Z = a_0 + a_{1xi} + a_{2xj} \quad 10$$

where $X_1 = ln[R\lambda_i - R_\infty(\lambda_i)]$ and λ is the wavelength. The algorithm corrects for a range of
variations in both water attenuation and bottom reflectance using a linear combination of the logtransformed radiances in the blue and green channels. Lyzenga model has essentially attempted to account for unpredictability in bottom type by using multiple spectral bands. A variable, Xj, was defined for each of the N bands as:

$$X_j = ln(L_j - L_{wj}) \quad 11$$

where, Lj = above-surface reflectance in band j and Lwj = averaged deep-water reflectance. The reflectance values were log transformed to create a linear relationship between input reflectance and depth. Deep-water reflectance was used to account for reflection because of surface effects and volume scattering in the water column and was assumed to result mostly from external water reflection, including sun-glint effects, and atmospheric scattering. However, the effect of deep-water radiance was almost negligible in shallow water bodies. To account for water quality heterogeneity and depthindependent variability in reflectance values between bands this algorithm was updated by Lyzenga et al., (1998).

Conclusion

Due to the advancement of technology applications such the utilization of acoustics, optics, and radar, bathymetry derivation technology has advanced significantly over the past century. To validate RS based models for the derivation of bathymetry in distant areas of the earth, more acoustic depth soundings are needed. However, the current review largely focuses on the many methods and technologies developed for bathymetric derivation, as well as the benefits of various bathymetric algorithms. RS approaches for bathymetry derivation can be divided into two categories: active RS/passive RS and non-imaging/imaging.

Due to technical limitations, the non-imaging LIDAR approach is not frequently employed for practical applications even though it is capable of accurately detecting elevations at sampled locations. In clean open waters, the LIDAR approach can calculate depths up to 65 m with an accuracy of 15 cm (Shridhar et al., 2015). Bathymetric mapping over relatively limited geographic areas is suited for airborne LIDAR. Turbidity in the water also limits LIDAR accuracy and application. The passive optical imaging method, in contrast, offers greater flexibility because it can be applied either analytically or empirically.

Since analytical modeling calls for the input of in-situ observed quantities linked to the optical characteristics of water, its implementation is complicated. As empirical modeling just needs a small number of in-situ measurements at certain sample locations, it is significantly simpler to apply. Under some conditions, this implementation may yield results with an accuracy comparable to that of analytical or semi-analytical implementations. Both broad oceanic waters and shallow, turbid coastal seas are amenable to the passive imaging techniques. For an efficient bathymetric derivation, choosing the best bathymetric algorithm is just as crucial as choosing the best image sensors. Each used model or sensor has strengths and weaknesses. The majority of the case studies have made use of optical data from satellites like Quick Bird, SPOT, Landsat, and IKONOS. In general, the Lyzenga model (linear band model) used for Quick Bird data can produce a sea depth error of roughly 9.7%, whereas the RMS for IKONOS is 2.3 m. Using a linear combination of the log-transformed radiances in the blue and green spectral channels, the Lyzenga method adjusts for a variety of variations in both water attenuation and bottom reflectance.

Less than 25 meters of water can have depths retrieved using the Stumpf's model or ratio transform model. In comparison to the linear band model, it also performs better when scattering turbidity (St In water depths between 15 and 20 meters, the ratio model is found to be slightly less noisier and can always resolve fine morphology properly. In general, it was discovered that the ratio transform was less reliable than the linear transform. Jupp's, Stumpf, and Lyzenga models were occasionally utilized when depths of less than 30 m were discovered using various approaches. Based on in-situ data, the empirical model (SPOT-5 imaging) may produce an accuracy of 0.5m. The stumpf's model outperforms the lyzenga and jupp models in terms of precision and test stability in shallow seas, where empirical fitting is time-efficient but requires real-time high-density depth soundings to get precise results. sumpf et al. 2003).

Bathymetry derivation accuracy was generally found to be depth dependent, with more mistakes being shown at deeper depths and fewer errors occurring at shallower depths. In general, optical RS models used for mapping the bathymetry have a number of advantages as well as some drawbacks. With adequately representative training data sets, two of the algorithms—Linear/Lyzenga and Ratio/Stumpf—are found to be more effective in determining the shallow depth in severely turbid seas.

Because the ratio transform approach or Stumpf model uses fewer empirical coefficients, it is easier to employ and more reliable across a wider range of geographic areas. In a non-homogeneous setting, the ratio model is more reliable. In comparison to the linear transform, the ratio transform has drawbacks, especially when there is more noise present. The Lyzenga linear band model, on the other hand, uses two or more bands, allowing for the separation of depth variations from bottom albedo variations while compensating for turbidity. When compared to stumpf's model, retrieval of bathymetry data under constrained environmental conditions is constrained.

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